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Inconsistent Wind Speed Trends in Current Twentieth Century Reanalyses

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Key Points:
- ECMWFs twentieth century reanalyses show strong upward wind speed trends
- The trends are also found in the assimilated wind speed data from ICOADS
- There is no equivalent trend in the NOAA 20CR reanalysis indicating large disagreement

Supporting Information:
- Supporting Information S1

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Abstract Reanalysis data underpin much research in atmospheric and related sciences. While most reanalysis only cover the last couple of decades, National Oceanic and Atmospheric Administration (20CR) and European Centre for Medium-Range Weather Forecasts (ERA20C and CERA20C) also developed reanalyses for the entire twentieth century that theoretically allow investigation of multidecadal variability. However, the approaches adopted to handle the massively evolving number of observations can cause spurious signals. Here we focus on wind speeds, as its assimilation is a key difference among these two products. We show that ERA20C and CERA20C feature significant trends in the North Atlantic and North Pacific wind speeds of up to 3 m/s per century. We show that there is a good relation between the trends in the reanalysis and assimilated wind speeds. In contrast, 20CR and the European Centre for Medium-Range Weather Forecasts free model run ERA20CM do not show positive trends in the same regions. As a consequence, conclusions drawn from any single twentieth century reanalysis should be treated cautiously in particular in sectors with a strong wind dependency (e.g., wind energy).

Plain Language Summary Many areas of human activity are directly influenced by the climate, and an enhanced understanding of its variability is hence beneficial for the society. We need long-term climate data sets in order to quantify and understand climate variability better. As of today, there are two centers that provide gridded climate data sets for the last century (so called twentieth century reanalysis). Deriving these data sets is intricate because the number and quality of observations has changed dramatically during the period of interest. In our study, we show that the data sets disagree strongly with respect to long-term wind speed trends. As the climate system is highly coupled, other climatic variables are likely also affected. We analyze the underlying observational data, and we can show that the upward trends in one data set also exist in the observations. Furthermore, we can rule out that the model itself created the trends. By comparison with earlier studies, we argue that the trends are likely spurious (i.e., not real) but some uncertainty remains. We recommend that climate impact assessments should be based on data from both centers. In future research projects, attempts must be made to resolve the strong discrepancy between the data sets.

1. Introduction

The climate system shows variability on various time scales in many interconnected components, for example, the atmosphere (Williams et al., 2017) and the oceans (Keenlyside et al., 2015). Improved understanding of these variations is essential for climate assessment, in particular regarding the identification of dominant modes of variability and for the separation of natural climate variability and anthropogenic climate change. It is also highly relevant because of the impacts of climate variability on society. For example, the design and management of energy infrastructure is directly affected by climate variability (e.g., Bloomfield et al., 2016; Conway et al., 2017; Wohland et al., 2018) and climate change (Schlott et al., 2018; Wohland et al., 2017). Incorporating climate variability into transmission system design (e.g., Kempton et al., 2010) and wind park siting (e.g., Grams et al., 2017) facilitates integration of wind energy. Relevant temporal scales range from subseconds (e.g., Schäfer et al., 2018), over diurnal, synoptic and interannual (e.g., Zubiate et al., 2017), up to multidecadal and centennial timescales (Bett et al., 2017). The last two have received relatively little attention and are therefore the focus of this study.

A meaningful quantification of climate variability requires sufficiently long data sets. Reanalysis data sets are often considered an ideal compromise between nongridded observations and gridded model output. They typically provide climate variables on regular grids and time intervals, and that follow available observations (taking into account the uncertainties). An introduction to the concept of data assimilation is given in Carrassi et al. (2018). Most reanalysis cover only a couple of decades as they rely on a large number of observations that are not available for a longer time span. Driven by the demand from end users and operational centers, the National Oceanic and Atmospheric Administration (NOAA) in the United States and the European Centre for Medium-Range Weather Forecasts (ECMWF) developed centennial reanalyses based on the relatively sparse data coverage. However, discrepancies among reanalyses can be large when data are scarce, because of the differences in models and data assimilation. Given the extensive usage of these reanalyses across and beyond the geosciences, such discrepancies would have major impacts on scientific results.

In this paper we address the issue of disagreeing wind speed trends in current twentieth century reanalyses. Our aim is to investigate wind speed trends in the different reanalysis products, to understand these trends in the context of the assimilated observations, and to comment on their trustworthiness. We show that the disagreement is linked to the assimilation of marine surface winds, which is only performed in the ECMWF reanalyses. Our results have implication beyond wind applications and may explain several issues identified in previous analysis, such as reported drifts and discontinuities of ocean heat content (Laloyaux et al., 2016), trends in Arctic mean sea level pressure (MSLP; Bloomfield et al., 2018), and disagreeing long-term trends in cyclones and wind storms (Befort et al., 2016). Moreover, trends in wind speeds are expected to impact other societally relevant fields such as energy, the water cycle (McVicar et al., 2012), and food chains in the oceans (Kahru et al., 2010). We seek to raise awareness among users and provide feedback for the developers of the data set since “reanalysis is an ongoing activity that should never be regarded as completed” (Laloyaux et al., 2016).

2. Data and Methods

2.1. Ensemble of Twentieth Century Reanalyses

We base our assessment on the full set of currently available reanalyses that span at least the period from 1900–2010. The set consists of the NOAA 20CR data set (Compo et al., 2011) and three different products from ECMWF, namely, ERA20CM (Hersbach et al., 2015a), ERA20C (Poli et al., 2016), and CERA20C (Laloyaux et al., 2018). All of them are widely used. Throughout the manuscript, we use (C)ERA20C to refer to ERA20C and CERA20C. 20CR and ERA20C are atmospheric reanalyses that take ocean variables as boundary conditions, whereas CERA20C is a coupled reanalysis that explicitly resolves the oceans (and other components of the climate system such as sea ice). ERA20CM, in contrast, is a free model run of the same atmospheric model used for ERA20C and constraint by the same boundary conditions. We include ERA20CM even though it is not a reanalysis because a comparison between ERA20C and ERA20CM allows to isolate the effects of data assimilation.

All reanalyses have been shown to be able to reproduce important modes of climate variability. 20CR agrees well with ERA-Interim (Dee et al., 2011) in terms of representing the North Atlantic Oscillation (NAO) and the Pacific Walker Circulation. It has also been shown that ERA20C has skill to reproduce, for example, NAO in the recent past (Poli et al., 2016). Its successor CERA20C is reported to feature significant improvements in the troposphere as compared to both ERA20C and 20CR (Laloyaux et al., 2018).

The assimilation strategy behind 20CR and (C)ERA20C differs substantially. While 20CR assimilates surface pressures only, both ERA20C and CERA20C also assimilate marine wind measurements. The number of pressure observations is capped in 20CR to minimize spurious effects of the increasing observation density. As a consequence of these main differences, Poli and National Center for Atmospheric Research Staff (2017) argue that 20CR is better suited in scarcely sampled regions, while ERA20C is believed to be superior in “well observed areas (…) where the assimilation of winds also assists to better represent synoptic systems.” In addition, CERA20C includes subsurface ocean temperature measurements and salinity profiles. The assimilated wind speeds are made available in an Observation Feedback Archive (OFA, Hersbach et al., 2015b).

Another difference lies in the ensemble size, which is large for 20CR (58) and smaller for ERA20CM and CERA20C (both 10). The smaller ensemble size for the ECMWF product could mean that the ensemble spread is not well suited to quantify uncertainty. In fact, Laloyaux et al. (2018) report that the CERA20C ensemble spread for wind speeds is too low to quantify the uncertainty by a factor of 2 to 3. This issue is exacerbated for ERA20C that is deterministic and hence has no ensemble.

All ECMWF products share the same resolution of roughly 1.125° · 1.125° (T159). The resolution of the older 20CR data set is coarser (roughly 1.875° · 1.875°, T62). Local topographic features such as individual mountains or the precise location of the coastline cannot be captured, potentially leading to massive uncertainties over small continental regions. In large areas over the oceans, however, the negligence of spatial details is likely of minor importance.

It is noteworthy that the ECMWF products are not independent and errors can hence propagate through the modeling chain. Both ERA20C and CERA20C make use of the ECMWF Integrated Forecast System (IFS). While ERA20C uses IFS CY38r1, CERA20C is based on the newer version IFS CY41R2, which allows for bidirectional interactions between the atmosphere and the ocean and thereby enables to capture dynamic feedbacks (Laloyaux et al., 2018; Poli et al., 2016). In both cases, a 24-hr assimilation window is applied. In addition, ERA20C uses background errors that are based on the ERA20CM ensemble and the 10-year CERA20C streams are in turn initialized from ERA20C data. All three ECMWF products are thus directly and indirectly connected. Nevertheless, there are also substantial differences. For example, the CERA20C background errors do not stem from the free model run ERA20CM as for ERA20C but are generated internally and are better suited to adapt to an evolving observational density by assigning flow-dependent background errors.

We base this study on the monthly mean 10-m wind speeds as the assimilation of wind speeds is one major difference between the data sets. For ERA20CM, unfortunately, the monthly average wind speeds have not been computed and archived (K. Hennermann, personal communication, March 2nd, 2018). We will therefore use the euclidean norm of the monthly mean wind components as a proxy for the wind speed. This leads to lower values because positive and negative values during a month can cancel each other out. We consider this approach justified because we focus on trends rather than absolute values.

2.2. Trend Assessment (1901–2010)

We perform linear least squares regressions for the annual and seasonal wind speed averages in Python based on the scipy.stats.linregress function. We consider a trend significant if a Wald Test yields a p value of less than 0.01 for the Null Hypothesis of no trend (i.e., 99% confidence level). For ERA20CM and CERA20C, we report the ensemble mean trend if at least 9 out of 10 ensemble members show significant trends of the same sign. Since ERA20C is deterministic, an ensemble assessment is not feasible. Although 20CR comes with a large ensemble, we restrict the analysis to the ensemble mean here. There can be trends in the ensemble mean that are not robust across the ensemble and such trends would be rejected if the full set of information was considered. As a consequence, the trends reported for 20CR are to be considered an upper bound in the sense that some of them could become nonsignificant if ensemble agreement in 20CR was accounted for. However, as we will see later, the main difference between the reanalyses is that (C)ERA20C features upward trends where 20CR either shows no or negative trends. This disparity can not be resolved by including the full 20CR ensemble because the more stringent trend condition will neither make nonsignificant trends significant nor will it flip signs of trends. Another reason to focus on the ensemble mean for 20CR is that we did not intend to repeat the assessment of Bett et al. (2017). Focusing on Europe, they find weak to no trends in the 20CR data set.

We define two focus regions in which the temporal evolution of the relationship between the observations and (C)ERA20C is studied in detail. They are referred to as North Atlantic (25–55°N, 50–20°W) and North Pacific (35–50°N, 180–130°W) and are displayed in Figure 1b. In a sensitivity test, we have also shifted the North Atlantic box northeastward by 10° (35–65°N, 40–10°W). Boxes are defined to be of similar size while capturing the most pronounced trends seen in the global maps. The trends are homogeneous inside the boxes in ERA20C such that the averaging procedure does not average out distinct spatial features (see Figure 1b). Within the boxes, annual time series of wind speed measurements are derived from the ship-based measurements that are assimilated into (C)ERA20C. To ensure that the entire annual cycle is sufficiently sampled, we only consider years with at least four measurements in all months. Without this constraint, increasing annual values could be rooted in an expansion of shipping activities into the winter months, an effect that has occurred over the twentieth century following technological innovations.

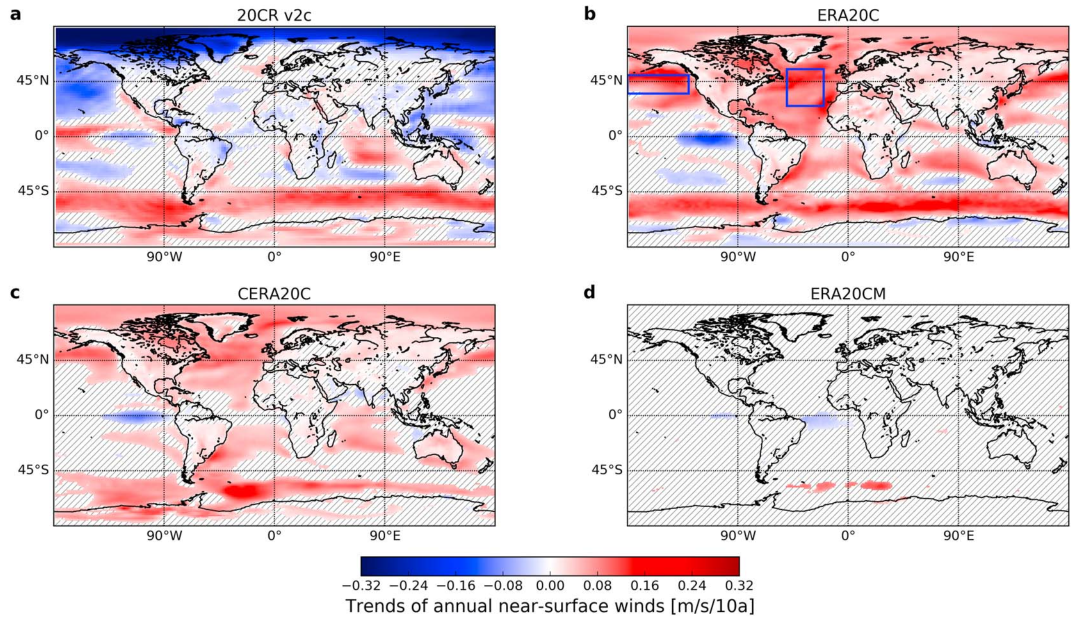

Figure 1. Maps of 10-m annual wind speed trends calculated from 1901 to 2010 for the different datasets (a–d). Colors denote trends that are statistically significant at the 99% level, and white-hatched regions mask out regions without statistically significant trends. In the case of ERA20CM and CERA20C, the ensemble mean trend is plotted if there is agreement across the ensemble with respect to the sign of change (9 out of 10). Focus regions for further assessment are given as blue boxes in (b) and are denoted as North Pacific and North Atlantic.

Lastly, we provide a gridded version of the trends of annual wind speeds in the observations. The measurements are projected onto the ERA20C grid by assigning each measurement to the nearest grid box. In addition to a required significance level of 99%, we only report trends if data in a grid box covers at least 60 years, begins no later than 1920, and ends no earlier than 2000, allowing for interruptions. This approach focuses on well-sampled regions and limits the effect of expanding shipping routes, while regions with occasionally missing data (e.g., due to World War 2) are not excluded. To quantify the relation between trends in the observations and the reanalysis, we compute four different measures. First, we calculate the pattern correlation p between trends in the observations and the reanalysis, considering only grid boxes where observations and model show significant trends: If $\text{trend}_{\text{OFA}}$ ($\text{trend}_{\text{REA}}$) denotes the trend in the OFA (reanalysis) and the index i samples all boxes that feature trends in OFA and the reanalysis, we define the pattern correlation as

$$p = r(\text{trend}_{\text{OFA}}, \text{trend}_{\text{REA}}), \tag{1}$$

where $r()$ denotes the Pearson correlation. Second, we define a binary classifier that predicts the sign of a trend in the reanalysis to be identical to the sign of the trend in the OFA for all boxes where the OFA shows a significant trend. The true positive rate (TPR) of this classifier is then computed as the number of correct predictions divided by the number of trends in OFA. Third, we quantify the fraction of grid boxes that feature trends in OFA but not in the reanalysis (NANR). Fourth, the total error rate is computed as the fraction of significant trends with opposing sign in OFA and the reanalysis.

3. Results

3.1. Disagreement of Wind Speed Trends in (C)ERA20C and 20CR (1901–2010)

In the ensemble mean of the 20CR reanalysis, we find decreasing centennial trends in the annual mean wind speeds over the North Pacific and the Arctic and increasing trends in the Southern Ocean (see Figure 1a). Over land, trends are largely absent. In particular, there are no trends in continental Europe and relatively weak trends west of Great Britain; this is in agreement with two earlier studies (Bett et al., 2013, 2017).

In contrast to 20CR, ERA20C and CERA20C both show strong centennial upward trends in annual mean wind speeds over much of the globe (see Figures 1b and 1c). They are most pronounced over the oceans, particularly in the North Atlantic, the northern North Pacific, and the Southern Oceans. Albeit weaker, trends are also found over large parts of all continents. A comparison between the CERA20C and ERA20C

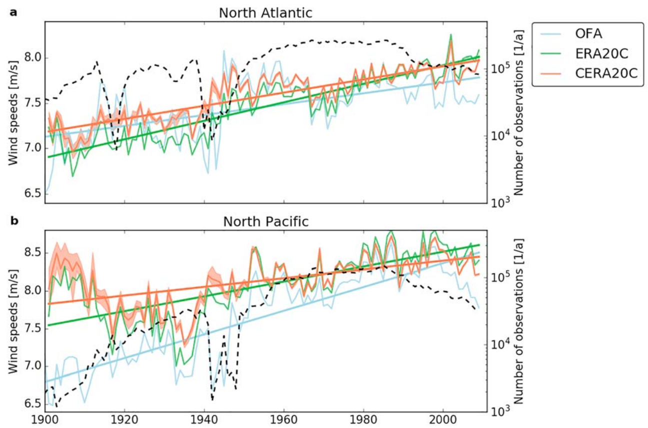

Figure 2. Wind speed trends over boxes in the North Atlantic and North Pacific for the assimilated observations (Observation Feedback Archive, OFA) and both European Centre for Medium-Range Weather Forecasts twentieth century reanalyses. CERA20C shading represents the full ensemble range while the line denotes the ensemble mean. The black dashed line represents the number of observations displayed on a logarithmic scale.

trends reveals that the magnitude of changes is reduced in the coupled reanalysis. This might hint to a dampening effect of the ocean or could be caused by the assimilation of subsurface ocean measurements. The overall pattern, however, remains unchanged.

Trends are absent almost everywhere in the free model runs ERA20CM (see Figure 1d), indicating that the trends are not a feature of the model or stem from the boundary conditions. Instead, they likely originate from the assimilation of wind speeds and/or sea level pressure data.

An assessment of the seasonal trends yields mostly the same results (see supporting information Figures S1–S4) . In particular, (C)ERA20C feature upward trends in the North Atlantic and the North Pacific in all seasons although the December, January, and February trend in CERA20C is relatively weak. In 20CR, the North Pacific downward trend is seen in all seasons except of December, January, and February and no season features widespread trends in the North Atlantic, although there are a few patches of upward and downward trends in June, July, and August. As for the annual values, the free model run ERA20CM is almost completely trend free for all seasons.

While 20CR and (C)ERA20C agree on the centennial trends of annual means in the Southern Ocean and the El Niño–Southern Oscillation region, there is considerable disagreement in most other areas. In particular, trends of opposite sign are reported for the Northern North Pacific. Similarly, in the North Atlantic (C)ERA20C shows a very clear upward trend, while 20CR does not feature significant trends. We will therefore investigate these two regions more closely. Since the assimilation of marine winds is one of the most important differences between 20CR and ERA20C, we will focus on the assimilated wind speeds in (C)ERA20C in the remainder of this paper.

3.2. Trends Also Present in Assimilated Wind Speeds

To test the hypothesis that wind assimilation is responsible for the disagreement between (C)ERA20C and 20CR over the North Atlantic and the North Pacific, we display time series of these two regions in Figure 2. In addition to the reanalysis wind speeds, the assimilated wind speeds from the ERA20C OFA are reported. For both regions, all three data sets show a significant upward trend between 1900 and 2010. The spread of the CERA20C ensemble is small at the beginning of the twentieth century (≈ 0.2 m/s) and decays to practically zero from 1950 onward. In the highly sampled North Atlantic, CERA20C and ERA20C follow the assimilated wind speeds very closely throughout the entire twentieth century. The results are large scale and do not depend on the precise location of the grid box as very similar results are found using a northeasterly shifted box (see supporting information Figure S6). In the North Pacific, the reanalyses deviate substantially from the OFA in the early twentieth century and around World War II. During these periods of sparse measurements, the observed wind speeds are distinctly lower than the reanalysis. This suggests that the wind speed assimilation pulls the models toward lower wind speeds in the first half of the century if the number of observations is high. If the data coverage in the early decades was higher, the reanalysis trends would thus likely be as high as the OFA trends. After WW2 and approximately between 1920 and 1935, the reanalyses are close to the assimilated wind speed observations also in the North Pacific. No significant trends are found in ERA20CM (not shown).

If the twentieth century is split in two parts, pre- and post-WW2, the trend assessment yields different results (see supporting information Figure S1). No significant trends are found in the North Atlantic OFA for either period. However, there is a substantial jump of wind speeds during WW2 and we are not aware of any physical justification of such a jump. Significant upward trends are still found for CERA20C (both periods) and for ERA20C (after WW2). The observational record indicates significant upward trends in the North Pacific for both periods. They are paralleled by the reanalyses after WW2. In the first decades of the twentieth century, significant downward trends are found in the reanalyses. They are most likely rooted in the exponential increase of observations between 1900 and 1930 (see Figure 2).

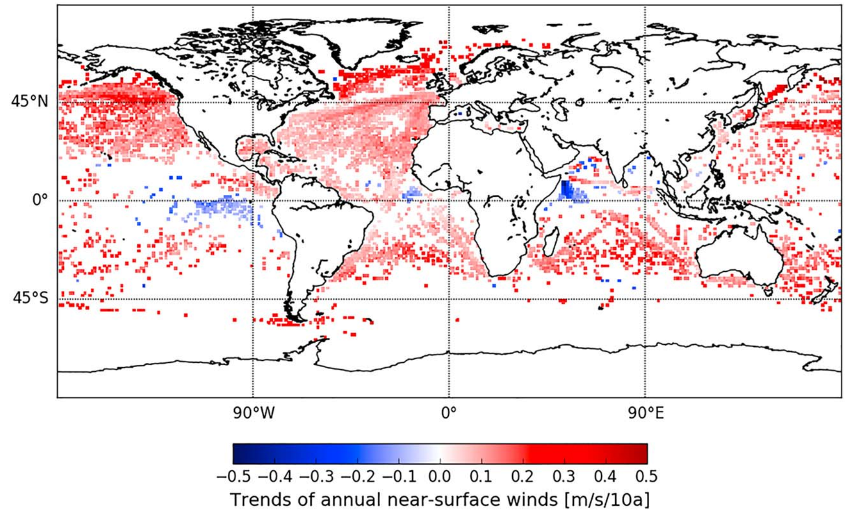

Figure 3. Trends in ship-based wind speed measurements that are assimilated in (C)ERA20C (projected onto the ERA20C grid). Trends are only displayed if significant at the 99% level and if the observations at each individual grid box fulfill these criteria: first measurement no later than 1920, last measurement not earlier than 2000, and at least 60 years of data.

Moreover, the gridded OFA wind speed trends (see Figure 3) show remarkable similarity with the (C)ERA20C trends (cf. Figure 1). In particular, there is a strong upward signal in the North Atlantic and the North Pacific and a downward trend in the eastern equatorial Pacific. Compared to the large extent of these areas, the error induced through gridding of the observations is negligible. The general dominance of positive over negative trends is supported by the OFA data. However, there are also some slight discrepancies, for example, off the Somalian coast in Eastern Africa. A quantitative analysis (see Table 1) reveals that positive trends in an OFA grid box translate into a positive trend in ERA20C (CERA20C) in at least 73% (60%) of the cases. More stringent data requirement in terms of minimum years of available observations lead to higher True Positive Rates, reaching up to 86% (74%). This substantiates a very strong relationship between the trends in OFA and the reanalysis output. The generally weaker agreement between OFA and CERA20C is due to fewer significant trends in CERA20C. For example, for 80 years of observations, the share of grid boxes that feature a trend in OFA but not in CERA20C (i.e., NANR) is 27% as compared to 12% in ERA20C. The higher share in CERA20C as compared to ERA20C can stem from disagreement across the ensemble or from the assimilation of ocean observations in CERA20C among others. The total error rate, interestingly, never deviates by more than 2% between ERA20C and CERA20C, highlighting that the increased share of grid boxes that feature a trend in OFA but not in CERA20C balances the decreased True Positive Rate. The main difference is thus fewer significant trends in CERA20C. Note that the share of grid boxes that feature a trend in OFA but not in the reanalyses decays with more stringent data requirements, which means that the best sampled trends in OFA are more often mirrored by trends in the reanalyses.

While OFA is a good predictor for the sign of trends in the reanalysis, there is only a mediocre pattern correlation between them ($0.37 \leq p \leq 0.48$) indicating a weak linear relationship. Since the models used

Table 1
Quantitative Assessment of Relationship Between OFA and Reanalysis Trends for Different Minimum Years of Available Observations

Years of observations	Pattern correlation p	TPR (%)	NANR (%)	TER (%)
60	0.39/0.45	73/60	12/27	15/13
80	0.45/0.48	75/62	12/27	13/11
100	0.42/0.37	86/74	6/19	8/7

Note. TPR is the true positive rate of a simple binary classifier as defined in section 2, NANR is the fraction of grid boxes with significant trends in the Observation Feedback Archive (OFA) and without trends in the reanalysis, and TER is the total error rate. Data are given for both reanalyses as ERA20C/CERA20C.

in the reanalyses are based on nonlinear dynamics and ensure fundamental principles of physics, such as the conservation of mass, reanalysis wind speeds cannot be expected to be a local linear function of OFA wind speeds. Instead, the precise wind speed value in any box is affected by the atmospheric dynamics in a larger region. The relatively small correlation values thus do not conflict with our basic argument that the reanalysis trends stem from the OFA trends.

4. Discussion—Are These Trends Real?

In light of the strong disagreement between data sets, we list known issues and findings that might help to judge the reanalyses' trustworthiness in the following paragraphs. To start with, there is a substantial amount of literature about spurious trends in wind speed measurements that arise due to changes in measurement techniques (e.g., Cardone et al., 1990; The WASA Group, 1998; Ward, 1992; Ward & Hoskins, 1996). Main aspects are increasing anemometer heights and the transition from estimated to measured wind speeds. Thomas et al. (2008) argue that trends in the ICOADS data set disappear if known biases are accounted for. Unfortunately, their analysis does not cover the entire twentieth century and they also report remaining trends in the period 1982–2002, which are still unexplained. Even though Cardone et al. (1990) report weaker wind speeds prior to 1950 after correction, they are still critical about the credibility of these trends. They argue that the changes may be due to a lack of standardization in measurements which is not captured by their correction. Apart from changes in the measurement technique, the sampling has also evolved considerably (see Figure 2).

Moreover, focusing on the Arctic Oscillation, a recent study finds that the ERA20C Arctic MSLP disagrees with the HadSLP2 observational data set (Bloomfield et al., 2018). While no trend is found in the observations, ERA20C features a significant downward trend in the Arctic, which increases the meridional pressure gradient over large parts of the Atlantic and the northern North Pacific. In other words, ERA20C features a MSLP trend that is consistent with the assimilated winds while being inconsistent with MSLP observations. In conclusion, it seems that the assimilated wind speed and MSLP observation disagree with each other. In order to reproduce the wind speed observations, unobserved MSLP trends are generated.

Over the Northern Hemisphere's continents, decreasing wind speeds are found since around 1980 with a rate of change of −0.7 m/s in 50 years (McVicar et al., 2012). This decrease is termed stilling and has been largely attributed to an increasing surface roughness (Vautard et al., 2010). It is likely that ECMWF has decided not to assimilate land-based wind measurements to avoid spurious downward trends in its reanalyses. Marine wind speeds are not affected via this process due to a very limited number of infrastructure projects at the ocean surface. Stilling seems to be inconsistent with the upward (C)ERA20C trends over land (see Figures 1b and 1c). However, surface roughness is virtually unchanged in all twentieth century reanalyses and (C)ERA20C is therefore not expected to feature stilling. In the real world, the downward trends due to surface roughness changes would be superimposed on the upward trend found in (C)ERA20C and the above mentioned studies would report the net effect.

In light of potential impacts of climate change on the wind energy sector, a couple of studies have looked into changing wind energy potentials over land. These studies are typically based on CMIP5 (Taylor et al., 2011) or downscaled projects such as EUROCORDEX (Jacob et al., 2014) and generally find small signals even under strong climate change scenarios. For example, Tobin et al. (2016) report changes of ±5% of European wind farm yields under the RCP4.5 and RCP8.5 scenarios based on EUROCORDEX. Based on statistical-dynamical downscaling of a large CMIP5 ensemble, Reyers et al. (2015) also report uncertain signs of changes in wind energy yields. The strong (C)ERA20C trends are hence unrealistic if the CMIP5 ensemble is considered trustworthy.

However, there are also reasons not to reject the (C)ERA20C trends as unrealistic. While the wind speed measurement technique has evolved dramatically over the last century, the method to estimate significant wave heights has changed less. Gulev and Grigorieva (2004) find significant long-term trends in wave heights in the North Pacific, which supports the wind speed trends reported here. In the North Atlantic they report significant changes for the second half of the last century only. In an effort to combine wind and wave height measurements, Tokinaga and Xie (2011) provide a corrected data set for the period 1950–2008. They adjust for increasing anemometer heights, employ Lindau's equivalent wind scale, and correct for known disparities in the daily cycle of visual observations. While these adjustments reduce the trends in wind speeds by roughly a factor of four as compared to the unadjusted ICOADS data set, a significant trend remains in the globally averaged wind speeds.

Moreover, Torralba et al. (2017) compare wind speed trends in modern reanalyses in 1980–2015. They report a few locations where significant trends occur in ERA-Interim, MERRA2, and JRA55. They are mostly located over the oceans and dominantly show upward trends. Apart from a section of the Southern Ocean, the trends generally do not agree with our results. In particular, they do not find a robust signal over the North Atlantic or the Northern North Pacific. However, in light of multidecadal variability, the short considered time span might prohibit assessments of long-term trends. For example, Siegismund and Schrum (2001) reported a strong upward trend in the North Sea based on the National Centers for Atmospheric Prediction/National Center for Atmospheric Research reanalysis between 1958 and 1997, which largely disappears if an extended period 1948 to 2014 is used as input (Stendel et al., 2016). The reason that these two studies estimate different trends may well be connected to low-frequency variability of the NAO (e.g., Hurrell et al., 2001). The biggest positive NAO trends associated with its multidecadal fluctuations were observed between 1960 and 1995 (Omrani et al., 2014), and the expansion of the period to 1948–2014 will counteract the positive NAO trend due to the recent negative NAO trend since 1990s. The significance of these NAO fluctuations is supported by studies showing that the decadal variations in seasonal forecast skill are linked to it (Scaife et al., 2014; Weisheimer et al., 2017). The long-term trends in winds identified here are not likely caused by the multidecadal variability: the trend has much larger amplitude than expected from the muldtidecadal variations (see Figure 2). Furthermore, the 110-year period considered in this study reduces the aliasing affect of multidecadal variability on the estimation of long-term trends.

Overall, aspects that challenge the trustworthiness of the (C)ERA20C trends dominate. They come from independent lines of evidence including highly trusted sea level pressure measurements, an evolving measurement technique of marine wind speeds, land-based wind speed measurements, and climate models. Nevertheless, there is no strict proof that the trends are wrong and even some indications that they might be right. The trends can thus not be refuted with certainty at the moment.

5. Conclusion

We report strong upward wind speed trends in the ERA20C and CERA20C reanalyses that generally do not agree with trends in 20CR. Similar trends are not found in the free model runs ERA20CM. We show that there is a close agreement between the presence of the wind speed trends and the assimilated wind speed data in ERA20C and CERA20C. Therefore, the trends in the reanalyses most likely originate from the assimilated wind speeds.

The trends may be spurious and due to evolving wind measurement techniques. Moreover, Bloomfield et al. (2018) report a spurious MSLP trend over the Arctic, which hints to a disagreement between the assimilated MSLP and wind speed data. The trends also disagree with land-based wind measurements, which feature downward trends in the last couple of decades. However, visual wave height estimations independently support some of the wind trends such that they cannot be fully ruled out as unrealistic.

Since the Earth system is interconnected in many ways, the trends in wind speeds will likely impact other climatic variables. We thus conclude that assessments of historical long-term trends or low-frequency variability from any single twentieth century reanalysis may be boldly misleading. We stress that it is important to recognize the great uncertainties in long-term wind trends and that more work is required to resolve this issue. For the time being, we suggest that any long-term impact assessment ought to be based on an ensemble of twentieth century reanalysis that at least consists of one member of 20CR and either ERA20C or CERA20C.

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References

Befort, D. J., Wild, S., Kruschke, T., Ulbrich, U., & Leckebusch, G. C. (2016). Different long-term trends of extra-tropical cyclones and windstorms in ERA-20C and NOAA-20CR reanalyses: Extra-tropical cyclones and windstorms in 20th century reanalyses. *Atmospheric Science Letters*, *17*(11), 586–595. https://doi.org/10.1002/asl.694

Bett, P. E., Thornton, H. E., & Clark, R. T. (2013). European wind variability over 140 yr. *Advances in Science and Research*, *10*, 51–58. https://doi.org/10.5194/asr-10-51-2013

Bett, P. E., Thornton, H. E., & Clark, R. T. (2017). Using the twentieth century reanalysis to assess climate variability for the european wind industry. *Theoretical and Applied Climatology*, *127*(1-2), 61–80. https://doi.org/10.1007/s00704-015-1591-y

Bloomfield, H. C., Brayshaw, D. J., Shaffrey, L. C., Coker, P. J., & Thornton, H. E. (2016). Quantifying the increasing sensitivity of power systems to climate variability. *Environmental Research Letters*, *11*(12), 124025. https://doi.org/10.1088/1748-9326/11/12/124025

Bloomfield, H., Shaffrey, L., Hodges, K. I., & Vidale, P. L. (2018). A critical assessment of the long term changes in the wintertime surface arctic oscillation and northern hemisphere storminess in the ERA20C reanalysis. *Environmental Research Letters*, *13*, 94004. https://doi.org/10.1088/1748-9326/aad5c5

Cardone, V. J., Greenwood, J. G., & Cane, M. A. (1990). On trends in historical marine wind data. *Journal of Climate*, *3*(1), 113–127.

Carrassi, A., Bocquet, M., Bertino, L., & Evensen, G. (2018). Data assimilation in the geosciences: An overview on methods, issues and perspectives. *Wiley Interdisciplinary Reviews: Climate Change*, *9*(5), e535. https://doi.org/10.1002/wcc.535

Compo, G. P., Whitaker, J. S., Sardeshmukh, P. D., Matsui, N., Allan, R. J., Yin, X., et al. (2011). The twentieth century reanalysis project. *Quarterly Journal of the Royal Meteorological Society*, *137*(654), 1–28. https://doi.org/10.1002/qj.776

Conway, D., Dalin, C., Landman, W. A., & Osborn, T. J. (2017). Hydropower plans in eastern and southern Africa increase risk of concurrent climate-related electricity supply disruption. *Nature Energy*, *2*(12), 946–953. https://doi.org/10.1038/s41560-017-0037-4

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., et al. (2011). The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, *137*(656), 553–597. https://doi.org/10.1002/qj.828

Grams, C. M., Beerli, R., Pfenninger, S., Staffell, I., & Wernli, H. (2017). Balancing Europe's wind-power output through spatial deployment informed by weather regimes. *Nature Climate Change*, *7*, 557–562. https://doi.org/10.1038/nclimate3338

Gulev, S. K., & Grigorieva, V. (2004). Last century changes in ocean wind wave height from global visual wave data. *Geophysical Research Letters*, *31*, L24302. https://doi.org/10.1029/2004GL021040

Hersbach, H., Peubey, C., Simmons, A., Berrisford, P., Poli, P., & Dee, D. (2015a). ERA20CM: A twentieth-century atmospheric model ensemble. *Quarterly Journal of the Royal Meteorological Society*, *141*(691), 2350–2375.

Hersbach, H., Poli, P., & Dee, D. P. (2015b). The observation feedback archive for the ICOADS and ISPD data sets, 18. Shinfield Park, Reading: ECMWF.

Hurrell, J. W., Kushnir, Y., & Visbeck, M. (2001). The North Atlantic Oscillation. *Science*, *291*(5504), 603–605. https://doi.org/10.1126/science.1058761

Jacob, D., Petersen, J., Eggert, B., Alias, A., Christensen, O. B., Bouwer, L. M., et al. (2014). EURO-CORDEX: New high-resolution climate change projections for European impact research. *Regional Environmental Change*, *14*(2), 563–578. https://doi.org/10.1007/s10113-013-0499-2

Kahru, M., Gille, S. T., Murtugudde, R., Strutton, P. G., Manzano-Sarabia, M., Wang, H., & Mitchell, B. G. (2010). Global correlations between winds and ocean chlorophyll. *Journal of Geophysical Research*, *115*, C12040. https://doi.org/10.1029/2010JC006500

Keenlyside, N. S., Ba, J., Mecking, J., Omrani, N.-E., Latif, M., Zhang, R., & Msadek, R. (2015). North Atlantic Multi-decadal Variability—Mechanisms and predictability. In *Climate change: Multidecadal and beyond* (pp. 141). World Scientific Publishing.

Kempton, W., Pimenta, F. M., Veron, D. E., & Colle, B. A. (2010). Electric power from offshore wind via synoptic-scale interconnection. *Proceedings of the National Academy of Sciences*, *107*(16), 7240–7245. https://doi.org/10.1073/pnas.0909075107

Laloyaux, P., Balmaseda, M., Dee, D., Mogensen, K., & Janssen, P. (2016). A coupled data assimilation system for climate reanalysis. *Quarterly Journal of the Royal Meteorological Society*, *142*(694), 65–78.

Laloyaux, P., de Boisseson, E., Balmaseda, M., Bidlot, J.-R., Broennimann, S., Buizza, R., et al. (2018). CERA-20c: A coupled reanalysis of the twentieth century. *Journal of Advances in Modeling Earth Systems*, *10*, 1172–1195. https://doi.org/10.1029/2018MS001273

McVicar, T. R., Roderick, M. L., Donohue, R. J., Li, L. T., Van Niel, T. G., Thomas, A., et al. (2012). Global review and synthesis of trends in observed terrestrial near-surface wind speeds: Implications for evaporation. *Journal of Hydrology*, *416-417*, 182–205. https://doi.org/10.1016/j.jhydrol.2011.10.024

Omrani, N.-E., Keenlyside, N. S., Bader, J., & Manzini, E. (2014). Stratosphere key for wintertime atmospheric response to warm Atlantic Decadal Conditions. *Climate Dynamics*, *42*(3-4), 649–663. https://doi.org/10.1007/s00382-013-1860-3

Poli, P., Hersbach, H., Dee, D. P., Berrisford, P., Simmons, A. J., Vitart, F., et al. (2016). ERA-20c: An atmospheric reanalysis of the twentieth century. *Journal of Climate*, *29*(11), 4083–4097. https://doi.org/10.1175/JCLI-D-15-0556.1

Poli, P., & National Center for Atmospheric Research Staff, E. (2017). The Climate Data Guide: ERA-20C: ECMWF's atmospheric reanalysis of the 20th century (and comparisons with NOAA's 20cr). Retrieved from https://climatedataguide.ucar.edu/climate-data/era-20c-ecmwfs-atmospheric-reanalysis-20th-century-and-comparisons-noaas-20cr

Reyers, M., Pinto, J. G., & Moemken, J. (2015). Statistical-dynamical downscaling for wind energy potentials: Evaluation and applications to decadal hindcasts and climate change projections. *International Journal of Climatology*, *35*(2), 229–244. https://doi.org/10.1002/joc.3975

Scaife, A. A., Arribas, A., Blockley, E., Brookshaw, A., Clark, R. T., Dunstone, N., et al. (2014). Skillful long-range prediction of European and North American winters: Scaife et al.: Predictability of the NAO. *Geophysical Research Letters*, *41*, 2514–2519. https://doi.org/10.1002/2014GL059637

Schäfer, B., Beck, C., Aihara, K., Witthaut, D., & Timme, M. (2018). Non-gaussian power grid frequency fluctuations characterized by Lévy-stable laws and superstatistics. *Nature Energy*, *3*, 119–126. https://doi.org/10.1038/s41560-017-0058-z

Schlott, M., Kies, A., Brown, T., Schramm, S., & Greiner, M. (2018). The impact of climate change on a cost-optimal highly renewable European electricity network. *Applied Energy*, *230*, 1645–1659. https://doi.org/10.1016/j.apenergy.2018.09.084

Siegismund, F., & Schrum, C. (2001). Decadal changes in the wind forcing over the North Sea. *Climate Research*, *18*(1-2), 39–45.

Stendel, M., van den Besselaar, E., Hannachi, A., Kent, E. C., Lefebre, C., Schenk, F., et al. (2016). Recent Change - Atmosphere, *North Sea region climate change assessment* (pp. 55–84). Cham: Springer Nature.

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2011). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, *93*, 485–498.

The WASA Group (1998). Changing waves and storms in the Northeast Atlantic? *Bulletin of the American Meteorological Society*, *79*(5), 741–760. https://doi.org/10.1175/1520-0477(1998)079<0741:CWASIT>2.0.CO;2

Thomas, B. R., Kent, E. C., Swail, V. R., & Berry, D. I. (2008). Trends in ship wind speeds adjusted for observation method and height. *International Journal of Climatology*, *28*(6), 747–763. https://doi.org/10.1002/joc.1570

Tobin, I., Jerez, S., Vautard, R., Thais, F., van Meijgaard, E., Prein, A., et al. (2016). Climate change impacts on the power generation potential of a European mid-century wind farms scenario. *Environmental Research Letters*, *11*(3), 34013. https://doi.org/10.1088/1748-9326/11/3/034013

Tokinaga, H., & Xie, S.-P. (2011). Wave- and anemometer-based sea surface wind (waswind) for climate change analysis*. *Journal of Climate*, *24*(1), 267–285. https://doi.org/10.1175/2010JCLI3789.1

Torralba, V., Doblas-Reyes, F. J., & Gonzalez-Reviriego, N. (2017). Uncertainty in recent near-surface wind speed trends: A global reanalysis intercomparison. *Environmental Research Letters*, *12*(11), 114019. https://doi.org/10.1088/1748-9326/aa8a58

Vautard, R., Cattiaux, J., Yiou, P., Thepaut, J.-N., & Ciais, P. (2010). Northern Hemisphere atmospheric stilling partly attributed to an increase in surface roughness. *Nature Geoscience*, *3*(11), 756–761. https://doi.org/10.1038/ngeo979
Ward, M. N. (1992). Provisionally corrected surface wind data, worldwide ocean-atmosphere surface fields, and sahellan rainfall variability. *Journal of Climate*, *5*(5), 454–475.
Ward, M. N., & Hoskins, B. J. (1996). Near-surface wind over the global ocean 1949–1988. *Journal of Climate*, *9*(8), 1877–1895.
Weisheimer, A., Schaller, N., O'Reilly, C., MacLeod, D. A., & Palmer, T. (2017). Atmospheric seasonal forecasts of the twentieth century: Multi-decadal variability in predictive skill of the winter North Atlantic Oscillation (NAO) and their potential value for extreme event attribution: Atmospheric Seasonal Forecasts of the Twentieth Century. *Quarterly Journal of the Royal Meteorological Society*, *143*(703), 917–926. https://doi.org/10.1002/qj.2976
Williams, P. D., Alexander, M. J., Barnes, E. A., Butler, A. H., Davies, H. C., Garfinkel, C. I., et al. (2017). A census of atmospheric variability from seconds to decades: A census of atmospheric variability. *Geophysical Research Letters*, *44*, 11,201–11,211. https://doi.org/10.1002/2017GL075483
Wohland, J., Reyers, M., Märker, C., & Witthaut, D. (2018). Natural wind variability triggered drop in German redispatch volume and costs from 2015 to 2016. *PLOS One*, *13*(1), e0190707. https://doi.org/10.1371/journal.pone.0190707
Wohland, J., Reyers, M., Weber, J., & Witthaut, D. (2017). More homogeneous wind conditions under strong climate change decrease the potential for inter-state balancing of electricity in Europe. *Earth System Dynamics*, *8*(4), 1047–1060. https://doi.org/10.5194/esd-8-1047-2017
Zubiate, L., McDermott, F., Sweeney, C., & O'Malley, M. (2017). Spatial variability in winter NAO–wind speed relationships in western Europe linked to concomitant states of the East Atlantic and Scandinavian patterns. *Quarterly Journal of the Royal Meteorological Society*, *143*(702), 552–562. https://doi.org/10.1002/qj.2943